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CROPS DIAGNOSIS USING HURST EXPONENT VALUES IN FIELDS IMAGE ANALYSIS

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ABSTRACT

One of the branches of sustainable agriculture is the precision farming which assumes an individual approach to each plant. The main problem encountered by the precision agriculture is to quickly acquire and analyze good quality data assessing the condition of the crop. One of the fastest growing monitoring techniques is the analysis of images obtained from cameras placed on UAV. The studies used the chaos tools to determine Hurst exponent values received from images collected during UAV flights over the fields. The obtained results of image analysis indicated the presence of a strong dependency between the Hurst exponent values and state of crops. Images showed crops which are in good standing have been seen as strong organize objects represented by the mean Hurst exponent values from 0.8 to 0.87. Crops in which occurred the destruction of plants on the collected images were estimated by the Hurst exponent between 0.41 and 0.49 values, which indicates the presence of the characteristics of chaotic changes in the distribution of color attributes.

INTRODUCTION

The proper application of the sustainable agriculture is only possible through receive of the accurate information about the crop status and soil fertility. The reliable information on the status of the crop is the key data needed to take further action in it (Christy, 2008). For large fields or fields unable to monitoring through traditional methods, one of the most popular method recognize of the state of crops is analysis of the images, had sent from satellite or UAV (Unmanned Aerial Vehicles). Optical recognized methods are one of the most promising for evaluation both state of crops and the soil conditions (Shapira et al., 2013). The principal advantage of the optical methods is the high speed of measures not possible for traditional ground methods (Zwiggelaar, 1998). It is well known that in the sustainable agriculture the time is the major parameter beside of the accuracy. Compared to the traditional soil or crops measurement methods, optical methods can reduce of the total of the estimation costs up to 80-90% for large areas (Nduwamungu et al., 2009).The main indicator have used for crops state evaluation has been the NDVI index (Normalized Difference Vegetation Index). NDVI index is described as relative difference of the reflectance values of infrared and red color wave (Soliman et al., 2013). For the better discrimination, the Infrared images are supplemented by images captured in visual light range. Interpreting of these images, the very significant for correctively recognize and estimation state of crops (McNairn et al., 2009). The find the proper method for the image discrimination is the important challenge for manufacturers of the image analysis systems.

In order to discriminate elements contained in the image we can use its texture. A texture can be defined as the placement of individual color identifiers in the image space. In the image consisting of a set of ordered pixels with the parameters of the point A (x, y, z), where x and y represent the position of the point on the surface of the image and z is the parameter describing the color properties of the image (Zhao & Wang, 2016). During analyses, it is possible to pick out information about generally speaking the image texture described as:

- Contrasts between pixels.
- Image coarseness - represents the size of a single pixel in the image relative to the entire image.
- Regularity - is defined as the pattern uniformity variation of the analyzed image parameters on the surface of the image.
- Anisotropy - determines the degree of regularity variation along of the different image axes.

Numerous works show the possibility of describing the texture of a picture by using fractal dimension which can be a measure of its regularity. The fractal dimension represents the degree of self-similarity variation of given quantity (Ekielski, 2013). The Hurst exponent is related to the time function of self-similarity. Hurst exponent is a dimensionless quantity to estimate the self-similarity of events occurring in time series. Hurst exponent H for white noise is H = 0, for random variable distribution Hurst exponent H = 0.5. The value of H = 1 indicates the occurrence of a high trend value in the measured value variations. The digital image can be presented as a 2-D time process in which the time equivalent is the distance between successive pixels and the measured values; pixel color parameters A (x, y). For the time series image, it is bi-directional in the x and y directions (Ekielski at al., 2015, Zhu et al., 2015).

METHODS

The research consisted in assessing the degree of image structure arrangement collected from fields. The pictures were collected by low-ceiling drones target runs. Drones were equipped with cameras to collect images in the visible light. The study was conducted with a Sony alpha 6000 camera and a flight height of 150 m. The resolution of the image at the ground level was 15 cm.

There were designated characteristic areas of the field selected from the photos area. The selected area was 256x256 pixels in size. Each of the analyzed area had an offset of 10% of the field width. Hurst exponent was calculated by Brown's fractional moves. Let X (t) be a function of Brown's fractional moves, the value variation of this function in the direction α can be described in two-dimensional space as:

$$X_H\big(x + \Delta x \cdot cos(\alpha), y + \Delta x \cdot sin(\alpha)\big) \tag{1}$$

Brown's fractional movements describe the freedom of measured quantity variations depending the environmental conditions. If the function $X_H(t)$ is a function of the partial Brown motions, then it has an average zero value of the increment with the existing variability and the variance is described by the formula 2:

$$E([X(x + \Delta x) - X(x)]^2) \propto |\Delta x|^{2H} \tag{2}$$

Where H is the Hurst exponent, H∈<0,1>. H is the Hurst exponent displacement factor of Brown and as Pentland (1984) has shown, there is a direct relationship between the fractal dimension DF and the displacement function $V_H(x)$ described by equation 3:

$$DF = DT + 1 - H \tag{3}$$

where DT - is a topological dimension. If the Hurst exponent is in the range of 0.5 <H <1, then the random process becomes a process with a long memory. The coarseness parameter H varies from 0 to 1. When H is close to 0, the surface is rough (coarse), When the value of H approaches 1, the surface is relatively smooth.

When considering the two-dimensional surface of Brownian motion Fourier transform can be used (formula 4):

$$E\left(\left[V_H\left(x+\Delta x\cdot cos(\alpha), y+\Delta x\cdot sin(\alpha)\right)-V_H(x,y)\right]^2\right)\propto|\Delta x|^{2H} \qquad (4)$$

The exponent H is independent of the angle α. As Voss (1986) demonstrated, if these requirements are met for a two-dimensional power spectrum, then:

$$F_H(f,\theta)\propto f^{-\beta} \qquad (5)$$

Where$\beta = 2H + 2$

The Hurst coefficient was calculated using the Matlab v 2013 software, with RGB tested images, it was transformed into CieLab space (Ekielski et al., 2017). For L * (brightness) and a * (greenness) color channels, the Hurst exponent was calculated.

AIM OF THE STUDY

The aim of the study is to evaluate the use of Hurst exponent for the assessment of crop images.

RESULTS

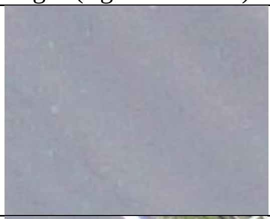
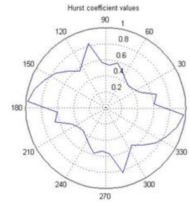
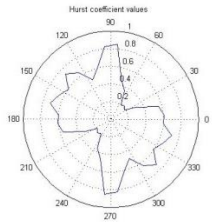
In the table 1 shown three of the analyzed RGB images (figures a, b, c).

Table 1.RGB images a, b and c captured during fields monitoring

a		b	
c			

Table 2 shows the images (figures a and b) of the studied surfaces and the corresponding directional distribution of the Hurst exponent. Of course, images showing large homogeneous areas have Hurst directional exponents near H = 0.5.

Table 2. Pictures of asphalt road surface and appropriately directional Hurst exponent values

	RGB images (figures a and b)	Diagram
a		
b		

In the case of areas covered by crops in good condition the Hurst exponent anisotropy stayed more uniformly for greenness (a*) canal, shown in the table 3.

Table 3. Images (a, b) are shown the growing wheat in the good condition

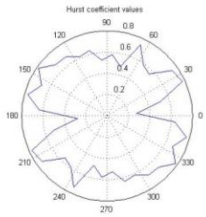
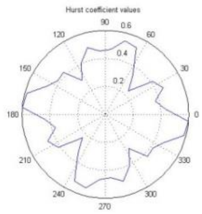
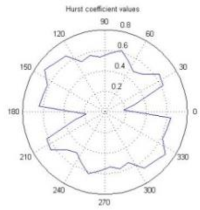
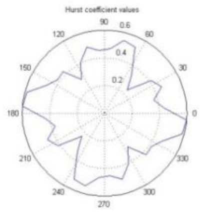
	Image (figures a and b)	Directional values for L* channel	Directional values for a* channel
a			
b			

Table 4. Changes in Hurst exponent of the diversified field surface structure

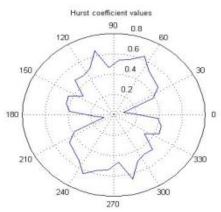
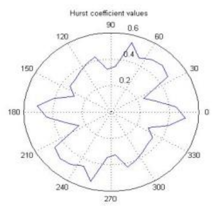
RGB image (figure a)	Directional values for L* channel	Directional values for a* channel
		

Table 5. Distribution of changes in parameter H in the case of directional mechanical damage (tractor wheels path).

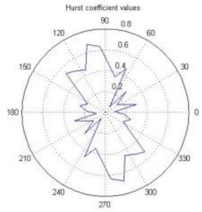
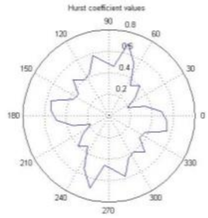
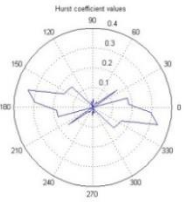
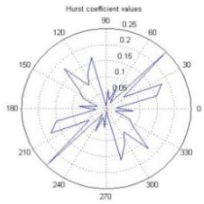
RGB image (figure a)	Directional values for L* channel	Directional values for a* channel
		

Table 6. Distribution of the H parameter on the field surface image after damages caused by atmospheric factors.

RGB surface image (figure a)	Directional values for L* channel	Directional values for a* channel
		

CONCLUSIONS

Texture description was always a difficult task when performing image analysis and automatic surface recognition. It is especially difficult in the automatic recognition of crop status, characterized by heterogeneity in color distribution. The study confirmed that nonlinear image analysis using the Hurst index as a parameter of the discontinuity of the examined texture image allows for searching. In the case of directional defects in the distribution of brightness parameters (L *) and the greenness channel (a *), the H value increases as the direction of the anisotropic distribution increases. The images of areas of continuous structure show high values of the H parameter, with their characteristic deviations in the direction perpendicular to the sowing line. Significant anisotropy of H distribution and lack of directionality of change characterize areas with poor condition caused by climatic factors. In conclusion, work has shown to have a significant effect of the image structure of moving drones on Hurst exponent. The calculated Hurst exponential directional distribution is an important additional parameter for assessing the condition of the examined area. High homogeneity areas are characterized by high Hurst values. Due in authors thought that one of the most important part of the image analysis by the Hurst's exponent is an anisotropy of its value distribution.

REFERENCES

Christy, C. D. (2008). Real-time measurement of soil attributes using on-the-go near infrared reflectance spectroscopy. *Comput. Electron. Agric. 61,* 9-10.

Ekielski, A., Żelaziński, T., & Durczak, K. (2017). The use of wavelet analysis to assess the degree of wear of working elements of food extruders. *Eksploatacja i niezawodność – Maintenance and reliability, 19 (4),* 561–565.

Ekielski, A., Mishra, P. K., & Biller, E. (2015). Utilizing fractal dimensions of extrudate sectional images for describing their textural properties. *SGEM. DOI: 10.5593/SGEM2015/B61/S25.088*

Ekielski, A. (2013). An algorithm for determination of threshold value in extruded products by the method of maximum increments: modification of Otsu method. *Ann. Warsaw Univ. Life Sci. - SGGW, Agricult. 62*, 71-79.

McNairn, H., Champagne, C., Shang J., Holmstrom D., & Reichert G. (2009). Integration of optical and synthetic aperture radar (SAR) imagery for delivering operational annual cropinventories *J. Photogram. Remote Sens. 64*, 434–49.

Nduwamungu, C., Ziadi, N., Parent, L. E., Tremblay, G. F. & Thuries, L. (2009). Opportunities for, and limitations of, near infrared reflectance spectroscopy applications in soil analysis: a review *Can. J. Soil Sci. 89*, 531–41.

Pentland, P. (1984). Fractal-based description of natural scenes, *IEEE Trans. Pattern Anal. Mach. Intell.*, PAMI-6, 661-674.

Shapira, U., Hermann, I.,Karnieli, A., & Bonfil D.J. (2013). Field spectroscopy for weed detection in wheat and chickpea fields. *International Journal of Remote Control, vol. 34, Nr 17,* 094-6108.

Soliman, A., Heck, R.J., Brenning, A., Brown, R., &Miller, S. (2013). Remote sensing of soil moisture in vineyard using airborne and ground-based thermal inertia data. *Remote Sensing vol.5,* 3729-3748.

Voss, R.,F. (1986). Random fractals: characterization and measurement. Scaling Phenomena in Disordered Systems, Vol. 133, 1–11.

Zhu, F., Meifeng, D., Conghua, X., Yuqing, S., Limin, L., (2015). Fractal descriptors based on quaternion Fourier transform for color texture analysis, Journal of Electronic Imaging, 24(4), 043004 (27 July 2015). DOI: 10.1117/1.JEI.24.4.043004

Zhao X., Wang X., (2016). Fractal dimension estimation of RGB color images using maximum color distance. Fractals 24,1650040. DOI: 10.1142/S0218348X16500407

Zwiggelaar, R. (1998). A review of spectral properties of plants and their potential use for crop/weed discrimination in row-crops. *Crop Protection, vol. 17,* 189-206.